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STUDIES OF MANUAL CONTROL SYSTEMS
Progress Report No. 3

for the Period 19 October 1963 to 18 April 1964

15 September 1964

Submitted to:

National Aeronautics and Space Administration
600 Independence Avenue
Washington, D. C. 20546

Attention: Dr. T. L. K. Smull

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I. INTRODUCTION

This is a report of work we have done under Contract NASw-668 during the six month period beginning October 19, 1963 and ending April 18, 1964, the last half of the first year of the contract.

We have worked on three problems under this contract: (1) development of mathematical models for the human controller; (2) investigation of the adaptive characteristics of the human controller; (3) investigation of multi-axis, multi-variable manual control systems.

During the first quarter of the contract we concluded an experimental investigation of human adaptive control characteristics and wrote a report which has been published as NASA Technical Note TN-D-2255, "The Adaptive Dynamic Response Characteristics of the Human Operator in Simple Manual Control," by Laurence R. Young, David M. Green, Jerome I. Elkind and Jennifer A. Kelly, dated April 1964.

During the second quarter we reviewed the literature on describing function models for the human controller and wrote a paper, "A Survey of the Development of Models for the Human Controller," by J. I. Elkind, which appeared in the book PROGRESS IN ASTRONAUTICS AND AERONAUTICS, Vol. 13, Pages 623-643, 1964.

During the last six months of this contract, the period with which this report is concerned, we have continued our work on the development of models for the human controller and have initiated an experimental investigation of multi-axis control systems. Our work on models was published in a paper, "Adaptive Characteristics of the Human Controller in Systems Having Complex Dynamics," by J. I. Elkind, J. A. Kelly and R. V. Payne, Proceedings of the Fifth National Symposium on Human Factors in Electronics, IEEE Professional Group on Human Factors in Electronics, 1964, San Diego, California. Whereas the first paper devoted to models was concerned primarily with continuous describing function models, this second paper is concerned with sampled-data models. The investigation of the multi-axis control that we have begun is an experimental study to determine the differences between single-axis and multi-axis control, and the effects on human controller performance of coupling among the control axes. We are particularly interested in the extent to which the single-axis models apply to multi-axis control. As of the end of the reporting period, we had performed only a few preliminary experiments.

II. INVESTIGATION OF MODELS FOR THE HUMAN CONTROLLER

The work that we have done on models during the period covered by this report is summarized well in the paper that we presented at the IEEE Meeting in San Diego. Accordingly, we include this paper as the principal part of this section on models.

ADAPTIVE CHARACTERISTICS OF THE HUMAN CONTROLLER IN SYSTEMS HAVING COMPLEX DYNAMICS

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Summary

A sampled-data model for the human controller in time-invariant control systems is proposed. The model is based on the Young eye movement and the Lemay-Westcott hand-tracking models. It has a pursuit channel that provides memory for making smooth almost continuous movements, a saccadic channel for making sudden step movements, and a force programmer for driving the muscle-hand system. The variable parameters of the model are identified and the model is extended to systems having time-varying controlled element dynamics in which the human controller adjusts his characteristics to compensate for the variations in these dynamics. Experimental data are presented which show that for sudden changes in dynamics the human controller's adaptive process is composed of four phases: (1) detection of a change, (2) stabilization, (3) reduction of accumulated errors, and (4) optimization of dynamics. Detection of a change in controlled element dynamics is based largely on the behavior of the tracking error signal. The times for detection, stabilization and reduction of accumulated errors can be reduced by cuing the controller when a change in dynamics occurs and giving him knowledge of and practice with the new dynamics. With proper cuing and when the subject knows the type of change in dynamics to be made, stabilization can be accomplished in about three sampling intervals. Optimization frequently requires considerable time to be completed, often as long as 10 to 20 seconds.

Author

Introduction

Our objective is the development and testing of models of the human controller in time-varying control systems, models of the process of human controller adaptation to changes in control system dynamics. A model for the time-varying situation should be built upon, or at least should include as a special case, a model of the human controller in time-invariant control situations. Although a number of such models have been proposed, none seem completely satisfactory as a basis for an adaptive model.[1-6] Accordingly, we have been led to the development of a new model, which, although not yet completely verified, has some interesting features.

In the development of this model we have tried to maintain a close correspondence between the structure of the model and the physiological structure and properties of the hand-tracking system. We have been led to a sampled-data model, because this formulation of the model appears to provide a more accurate representation of human controller characteristics than does a continuous model, and yet is amenable to analysis.

After presenting the model for the time-invariant situation, we discuss some experiments with time-varying control systems in which the controlled element dynamics underwent sudden changes. The process by which the human controller adapts to these changes in dynamics is examined and the time-invariant model is extended to include this adaptive behavior of the human controller.

A Model for the Human Controller in Time-Invariant Systems

The model we have developed was strongly influenced and contains many of the features of the Young model for eye movement control[5] and of the Lemay-Westcott model for compensatory hand tracking.[6] These models are reviewed briefly below. For a detailed description of them the reader is referred to the original papers.

A. Review of Models

1. The Young Model. A linearized form of the Young model is in Fig. 1a. It is a sampled-data model with two forward channels that operate on the sampled error $\epsilon^*(t)$. The sampler M has a period of T seconds. The saccadic channel

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produces a step response to an error after a delay T. The pursuit channel computes the first difference of the sampled error to estimate error rate and then responds continuously so as to produce a smooth, continuous output whose velocity is approximately equal to the estimated velocity. It is, therefore, a channel that has memory. It is, however, inoperative when the error rate is very large (greater than 30°/second) and does not respond to rates resulting from saccadic movements. (The non-linearity which inhibits response to targets moving with high velocity is not shown in Fig. 1a.)

In Fig. 1b are the responses of the saccadic, pursuit, and the combined (pursuit and saccadic) systems to step and ramp inputs. Typical values for the sampling interval and saccadic delay times, T, are 0.15 to 0.2 second.[5-7]

2. The Lemay-Westcott Model. In Fig. 2a is a flow diagram equivalent of the Lemay-Westcott model. It is also a sampled-data model. It has a predictor A + Bs which operates on the error, only a saccadic type of forward path which contains a delay T (represented by z in the figure), a zero-order hold (1-z)/s, and a force programmer which produces a pulse of accelerating force followed by a pulse of decelerating force as shown at the bottom of the figure. The model also has a feedback of the predicted response r_p of the muscle hand dynamics to the program of force about to be applied. This prediction is necessary in their model because the sampling interval T is one-half the sum of reaction time delay and movement time. The prediction feedback prevents the model from responding to an error detected during the previous sample for which a corrective movement is about to begin.

The response of the Lemay-Westcott model to a step and a ramp is shown in Fig. 2b. For the step, the predictor is assumed equal to 1. For the ramp, it is assumed equal to 1 + 2s. A typical sampling interval T is about 0.2 - 0.3 second. Note the staircase-like response to the ramp.

B. Specifications for a Hand Tracking Model

Neither the Young nor the Lemay-Westcott model is completely satisfactory for the hand tracking. Rather than discuss their deficiencies in detail, we will present characteristics that a satisfactory model should possess, support the necessity for these characteristics by reference to the literature or to examples of tracking data, and then present a flow diagram of the model that possesses these desired characteristics.

1. Perceptual Characteristics. As Bartley and others[8] point out, target displacement and velocity are primary perceptual quantities and appear to be perceived directly. The Young method of deriving velocity from displacement samples seems somewhat incorrect, although it has the advantage of providing an estimate of the average velocity during a sampling interval. Averaging seems necessary to avoid spurious velocity estimates resulting from irregularity in the error.

2. Intermittency. There are a number of arguments in favor of an intermittent or sampled-data model. Such a model allows naturally for a variation in reaction times, and leads to a rectangular distribution of reaction times,[6-9] which, although not an accurate approximation to measured reaction time distributions, is better than the fixed reaction time predicted by a continuous model. There is evidence in tracking records that responses are made intermittently (Fig. 3b), although, in continuous tracking a well-practiced subject often can respond smoothly without apparent intermittency (Fig. 3a). Such smooth tracking can be attributed to a smooth pursuit-like forward channel coupled to an appropriate force programmer. Note that in Fig. 1b, Young's intermittent model responds smoothly to ramp inputs.

3. Reaction Time, Movement Time and Sampling Interval. When tracking random steps with controlled element Y_c=K one often observes reaction times in the range 0.2 to 0.35 second[7] (Fig. 4). When tracking continuous random signals, the average delay in human controller describing functions is usually about 0.15 second.[1-2] No well-substantiated explanation for this discrepancy has been offered. The interaction between eye and hand movements in compensatory tracking may possibly be a contributing factor. When hand tracking in a compensatory system, the controller usually follows the target with his eyes if it is not moving too fast. When the target makes a step displacement his eyes move first onto the target and then he moves his hand. In such a case, the reaction time of the eye movement system may add to that of the hand system. When tracking a continuous signal, the target rarely leaves the fovea in the interval between samples and the eye movement reaction time should not enter into the hand system dynamics. According to this hypothesis, if we assume that the sampling processes of the eye and hand system are synchronized by the occurrence of the stimulus (step displacement of the

target), we would expect the hand reaction time distribution to be the same as the eye distribution plus about 0.15 second. In the eye and hand reaction time distributions obtained by Okabe et al[7] and plotted in Fig. 4, the hand reaction times are about 0.1 second longer than the eye reaction times. However, Okabe observed that eye movements are not necessary for step function tracking, but he apparently did not determine if there was a difference in hand reaction time when the eyes moved and when they did not. Further experimental work is required to establish the cause of the difference between step and continuous tracking.

Lemay and Westcott give 0.2 second as the time required to make the first movement in response to a step input. Yet, in continuous tracking one frequently observes movements as short as 0.1 second (Fig. 3b), with 0.15 second being a good estimate of the average duration. This difference between step and continuous tracking may result from a limit on the velocity of movements which causes a lengthening of the time for the initial movement in the response to a large step, but still permits short movements such as required for continuous tracking to be made in 0.15 second.

Lemay and Westcott use a sampling interval of 0.2 second in their model. This would lead to a peak in the system describing function at 2.5 cps, one-half the sampling frequency. Bekey[4] and Navas[9] found that in continuous tracking the sampling peak usually fell between 1.2 and 1.6 cps. This would suggest a sampling interval of about 0.3 to 0.4 second. However, the sampled-data model leads to a rectangular distribution of step reaction times whose width is equal to the sampling interval. For step inputs the hand system reaction times are concentrated in a 0.15 second wide region from 0.2 to 0.35 second,which suggests a sampling interval of 0.15 second. The discrepancy between these two values of the sampling interval might be resolved by postulating with Vince[10] a refractory mechanism that prevents additional samples from being taken, or at least from being processed, until the movement made in response to the previous sample has been completed. Such a mechanism would result in a sampling interval of about 0.15 second while the controller was waiting for a step input to occur, and a sampling interval of 0.30 second after he had initiated his response, assuming a movement time of 0.15 second. This kind of sampling would account for both the 0.15 second spread in reaction time and the 1.5 cps sampling peak in system describing function. It is interesting to note that Young, who obtained eye movement step function reaction times distributed largely between 0.2 and 0.4 second, observed a sampling peak in eye movement describing function at about 2.5 cps, which corresponds to a sampling interval of 0.2 cps. Eye system movement times are very short compared to reaction time.

4. Forward Channels. There is evidence of both a smooth pursuit as well as a saccadic channel in the hand-tracking system, despite assertations to the contrary by Navas.[9] Figure 5 gives an example of smooth pursuit-like tracking of a ramp input with $Y_c(s)=K$. In Fig. 6 is the response of the same system ($Y_c=K$) to a fairly fast parabolic input. Note that the stick response appears to be composed of straight-line segments with gradual transitions between them and one large saccadic movement. These elements of the response are also evident in the record of response rate. This result is characteristic of a first-order sampled-data system. Young obtained eye movement records very similar to those in Figs. 5 and 6. Thus, it seems necessary to include in our hand model a smooth pursuit channel that is very similar to the eye movement pursuit channel. It is also evident from step responses and other records that a saccadic channel should also be an integral part of the model.

The essential property of the pursuit channel is that it has memory. A single stimulus under most circumstances produces a continuous response of constant velocity. The saccadic channel does not have memory and a single stimulus generally produces a single step response.

5. Force Program. The concept of the force program is a very important contribution of the Lemay-Westcott model. The kind of force program used by the human controller depends upon the task, particularly upon the controlled element dynamics, $Y_c(s)$. In Figs. 3a, 3b and 3c are examples of controller stick movements for $Y_c(s)=K$, K/s, and K/s^2. For $Y_c(s)=K/s$ the stick movement is highly saccadic. This kind of movement could be produced by a "bang-bang" force program driving an inertial load as suggested by Lemay-Westcott. For $Y_c(s)=K/s^2$ (Fig. 3c) the basic movement appears to be less like a step and more like a triangular pulse, which would be roughly the derivative of the step-like basic movements observed for $Y_c(s)=K/s$ (Fig. 3b). By changing his force program in this way the controller is able to achieve rate compensation of the control loop.

6. Muscle and Hand Dynamics. For our purposes it seems sufficient to assume with Lemay and Westcott that the dynamics

of the hand and muscle are a pure inertia, $1/s^2$. These dynamics, together with the appropriate force program lead to movements that approximate closely those of the human controller. However, it should be recognized that such a simple representation of the muscle-hand dynamics do not take into account the closed-loop nature of the muscular control system and its variable characteristics, all of which play an important role in tracking performance. Houk[11] has developed a model for the motor control system and Navas[9] has applied it to manual tracking. We hope to incorporate their work in our model at some future time.

7. Prediction and Compensation. Two kinds of prediction appear to play an important role in manual control systems. One kind is a form of pattern recognition and reproduction in which the human operator reproduces some fairly complex target course that he has learned. This kind of operation is very important, but we are not yet prepared to deal with it.

The second kind of prediction is based upon perception of error and error rate, which are basic perceptual quantities. It has been shown in continuous input tracking studies that the relative weighting given to error and error rate in determining the response depend upon the input signal characteristics and the controlled element dynamics.[1-2] Results from continuous tracking studies and the tracking records of Fig. 3 indicate that we should not assume with Young that error rate drives only the pursuit channel and error only the saccadic channel. For the hand system it appears that the weighted sum of error and error rate appear to drive the saccadic system and the pursuit system. Both the relative weighting of error and error rate and the type of force program used determine the lead or lag compensation that the controller employs to stabilize and optimize the control system. We discuss this very important question of compensation in detail after we have presented and described the proposed model, which we do next.

C. Flow Diagram of Proposed Hand Tracking Model

The signal flow diagram for the model is in Fig. 7. It is very similar to Young's model in its two-channel structure and to the Lemay-Westcott model in its representation of the force program and muscle-hand dynamics. It differs from both of these models in a number of important respects.

Estimation of error rate is obtained by direct differentiation of the error to reflect the fact that velocity estimation is a primary perceptual quantity. There should probably be some low-pass filtering of the error rate signal, but we have omitted it for simplicity. Both the error rate and error are sampled by two periodic synchronized samplers M which we assume to operate with a sampling interval of 0.3 second when the system is active and responses are being made. When the human controller is quiescent and waiting for a signal (step or ramp, for example) to occur the sampling interval is 0.15 second. This accounts for the observed spread in reaction times to such signals. We have, however, omitted the additional delay that appears necessary to account for the long reaction times observed with step inputs. This delay does not appear in tracking continuous signals. The doubling of the sampling interval when the controller is active is attributed to a refractory mechanism. The 0.3 second interval would also account for the sampling peak at about 1.5 cps found in system describing functions when continuous signals are being tracked. The delay in both channels is 0.15 second, one-half the sampling interval, which corresponds to observed delays in continuous tracking. The memory is provided by a positive feedback with delay of one-quarter the sampling period. This loop produces a train of impulses when a non-zero sample of $\dot{e}$ is obtained as shown at the bottom of Fig. 7. This impulse train is operated on by the force program. If k_{f2} in the force program is zero, the pursuit channel impulse train produces a pair of equal and opposite rectangular pulses which drive the hand dynamics as shown at the bottom of Fig. 7. If k_{f1} is zero, two pair of equal and opposite impulses are produced as shown in Fig. 7. By varying the parameters k_{f1} and k_{f2}, the model can be made to exhibit the same kind of change in character of its response as does the human controller when the order of the controlled element dynamics is increased. Decreasing k_{f1} and increasing k_{f2} provides lead compensation. Lead compensation is also obtained through adjustment of the cross-coupling parameters k_{rs} and k_{mp} and the gain parameters k_p and k_s.

We know from studies of continuous tracking that when the controlled element is a simple gain, $Y_c(s)=K$, the human controller tends to make his response rate proportional to error magnitude. In such a case, the error magnitude would drive the pursuit system which in turn controls the rate at which the hand moves. The lead compensation parameters would all be zero except k_{mp}. The force program parameters would be $k_{f1}=1$ and $k_{f2}=0$. Hand movements would be mostly of the smooth kind seen in the tracking of ramps. In Fig. 3a is an example of a tracking record from a well-trained subject exhibiting these characteristics.

If $Y_c(s)=K/s$, we would expect that human controller output would tend to be proportional to error magnitude. Therefore, the error magnitude should drive the saccadic system and the pursuit system should be relatively inactive. This could be accomplished by making all lead compensation constants zero except k_s. The force program would still be the same as for $Y_c(s)=K$, but the hand movements would tend to be composed of saccades as shown in the tracking record of Fig. 3b.

If $Y_c(s)=K/s^2$, the human controller must provide lead in order to stabilize the system. This he can do by using error rate to drive the saccadic system and keeping the same force program. Alternatively, he could change the force program so that $k_{f1}=0$ and k_{f2} is a constant, and drive the saccadic system with error magnitude. We see examples of both types of behavior in the tracking records. In the tracking record of Fig. 8, the controller apparently used error rate to drive the saccadic system. In the record of Fig. 3c, the controller adopted the strategy of changing his force program to produce responses composed of a series of short pulses using error as the principal input to the saccadic system. This record was produced after considerable training during which the controller adopted the strategy of changing his force program to produce pulses. Early in his training he used the normal force program with error rate input. Fig. 8 is a typical example of this mode of behavior.

Note that feedback of predicted response is not necessary in the model, as was the case for the Lemay-Westcott model since a sample of the error is not taken until the previous response is completed. Also, it is not necessary to follow Young's procedure of including in the model special provisions to prevent the pursuit system from responding to error rates produced by the saccadic system. By making the sampling interval equal to the sum of reaction time and movement time, the saccades are completed before error rate is sampled.

Application to Time-Varying Systems

A. The Problem

Consider the following situation. The human controller is tracking in a one-dimensional compensatory control system in which the controlled element $Y_c(s)$ changes suddenly in an unpredictable way. $Y_c(s)$ is of three different forms: $\pm K$, $\pm K/s$ and $\pm K/s^2$ where K can take on any of several different values. The controller is familiar with all of these dynamics and has been trained to track them all proficiently. His task is to track the input signal which is a low-frequency (bandwidth 1.5 rad/sec) gaussian-like signal and when a change in dynamics occurs he presumably will change his own characteristics to compensate for the changes in system characteristics.

The problem of interest to us is to develop a model which will predict the nature of the human operator's adaptation to these changes in system dynamics. The model we develop is an extension of the time-invariant model for hand tracking shown in Fig. 7.

B. Features of an Adaptive Model

Let us describe in a qualitative way the principal features of human adaptation to changes in $Y_c(s)$. In Fig. 9 is a typical tracking record showing adaptation to a change in dynamics from $Y_c(s)=8/s^2$ to $=-16/s^2$. The transition in dynamics occurs at time t_o. At the time of the transition the error is small and the output velocity is well matched to that of the input signal for the next second. During this period the controller makes about two large corrective movements, but he does not detect the fact that the dynamics have changed. The error at transition is slightly negative and the controllers' movements are such that they would have reduced this negative error had the dynamics not changed. Because of the change in the polarity of the dynamics, these corrective movements instead tend to make the error more negative, but the input during this time is slowing down and more than compensates for this negative tendency in the error. In fact, the change in input velocity causes the error to drift toward zero, thus giving the controller the impression that his movements are appropriate to the system dynamics. As the input slows down even more, the error goes through zero and takes a positive value at time $t_o+1.0$ second, and the controller makes a small positive pulse-like movement starting from a negative base line so that its effect is that of a negative movement. He still has not recognized that the system dynamics have changed and this last movement causes an increase in error rate. The controller makes another movement in the same direction and makes the error larger. He then (at time $t_o+1.7$) realizes that the dynamics have changed and moves the stick hard over in the opposite direction. By time t_o+4, the controller has recovered from his previous mistakes and has the system more or less under control. He still has not completely adjusted his gain for the movements in the neighborhood of t_o+4 appear too large. Several more seconds are required for the amplitude of movement to be adjusted downward.

In Fig. 10 are describing functions for the relation between error and stick displacement that were computed from successive five second segments of these signals preceding and following a change in $Y_c(s)$ from $-4/s^2$ to $+8/s^2$. These describing functions were obtained using a multiple regression analysis method described in previous papers.[12-13]

The describing functions in Fig. 10 are for the same kind of transition as the time tracings in Fig. 9 - a gain doubling and a polarity change. For the five second period preceding the transition (t_o-5 to t_o) the describing function exhibits low-frequency lead that is evident in both the amplitude ratio and the phase. For the five second period starting at t_o+3 the phase has been reduced by 180 degrees reflecting the fact that the controller has detected the change in polarity of system gain and has reversed the direction of his movements. There is some lead compensation evident in both amplitude ratio and phase, but not as much as before. The amplitude ratio has been reduced by 9 or 12 db, indicating that the controller has over-compensated for the 6 db increase in the gain of $Y_c(s)$. For the next five second period, the one beginning at t_o+8, the controller has increased his gain so that total forward loop amplitude ratio (controller plus $Y_c(s)$) is about the same as it was before the transition. He also added a little phase advance so that the total forward loop phase characteristics are nearly the same as before the transition.

Figures 9 and 10 illustrate a number of important aspects of human adaptation to variations in controlled element dynamics. First the controller must detect the fact that the system has changed its characteristics and identify the change before he makes a major compensatory change in his characteristics. Then he must stabilize the closed-loop system by making appropriate changes in his characteristics. He then reduces accumulated errors. Finally, he adjusts his characteristics to optimize system performance.

1. Detection. Detection of a change in $Y_c(s)$ in a compensatory tracking task appears to be based simply upon the behavior of the error. It does not appear to involve more elaborate model matching or correlation techniques. Each movement that the controller makes should reduce the error or at least decrease its rate of increase. When several movements in succession lead to an increase in error, that is good indication that the dynamics have changed.

The time at which detection takes place cannot be determined directly. The best we have been able to do is to determine the point at which the controller starts to track differently from his tracking before the change. The interval between this time and the time of the change in dynamics we call detection time. The detection time interval thus includes some time which is really devoted to identification of system dynamics. Detection times were obtained from time tracings of input, error, stick movement and output such as Fig. 9.

It appears that the detection process can be represented by a very simple model consisting of a threshold detection process operating on the tracking error. The threshold is set to three times the standard deviation of the tracking error. Whenever the error exceeds 3σ, a change in system dynamics is assumed to have occurred. After detection the controller presumably has to make at least one movement to determine what characteristics the system now possesses so that he can change his mode of response.

In Table I are given average values for several different changes in $Y_c(s)$ of the elapsed time between the point at which the error exceeds the 3σ value (when the model would detect the change in dynamics), and the point at which the controller changes his response behavior, which point we have used as the time of detection. The average value for this interval is approximately 0.5 second. Eighty per cent of the observed intervals are between 0.3 and 0.6 second. An interval of 0.5 second is long enough for an average of one-and-one-half movements to two movements. At the end of this interval the controller has made at least a partial identification of the new system dynamics.

2. Identification. Once a change in dynamics has been detected, the first task of the controller is to get the system under control, that is, to get it to a stable operating condition. To do so, the controller must identify certain aspects of the change in dynamics. For the kind of dynamics that we are concerned with, $Y_c=\pm K$, $\pm K/s$, and $\pm K/s^2$, the identification problem is one of determining the polarity, order and gain of the controlled element.

We have postulated a number of simple mechanisms for identification of these dynamics. One such mechanism is composed of three simple tests on the error signal, each of which involves comparison of error and its rates of change with stick movement. The controller can perceive directly the change in error, Δe, and in error velocity, $\Delta\dot{e}$, resulting from a stick movement Δr. He can determine the change in error acceleration $\Delta\ddot{e}$ from successive samples of error velocity. We assume that the controller knows what stick movement Δr he has made.

The identification procedure is to compute the three ratios: $\Delta e/\Delta r$, $\Delta\dot{e}/\Delta r$, $\Delta\ddot{e}/\Delta r$. The first ratio will change sign whenever there is a polarity change. If this ratio is approximately constant then the dynamics are $Y_c(s)=K$. Similarly, if the second or third ratios are approximately constant $Y_c(s)=K/s$ or K/s^2, respectively. The magnitude of these constants determines the gain of the system. It is important to note that the identification process that we are discussing takes place with relatively large stick movements and large changes in error. Hence, there should be little masking introduced by the input signal or by errors in estimating the error and stick movement.

3. Stabilization. Polarity is clearly the first property of $Y_c(s)$ to establish since an uncompensated reversal of polarity results in a positive real closed-loop pole and, therefore, an exponential divergence. In all records of transitions involving a polarity change and a change in gain or order, the polarity is the first characteristic of the controller's response to be changed. This is almost always done by the time that we have designated as detection. Compensation for changes in gain and order frequently appear to be done concurrently, although there is some indication that the gain is the last parameter to be adjusted, but this cannot be determined unequivocally from our data. In Fig. 8, for example, we see that the controller has started to make the pulsatile movements characteristic of tracking with $Y_c(s)=K/s^2$ before he has made the final adjustment of gain.

Thus, by operating on the error signal alone and comparing derivatives of the error signal with the stick response, it is possible to identify all the changes in dynamics that we have investigated. These operations can be incorporated in the model of Fig. 7, with feedback to the parameters of that model to adjust them to the proper values. The adjustment procedure has not yet been determined, but the following is a reasonable procedure: (1) if the polarity has changed, reverse the polarity of k_{f1} and k_{f2} in the force program. If the order has changed, adjust the lead compensation constants and the force program constants so that they are appropriate to the new dynamics. The appropriate values of these constants are presumably known to the controller since he is well-trained in the control of all of the three types of $Y_c(s)$. Adjustment of gain would be accomplished by multiplying k_{f1} and k_{f2} by the inverse of the appropriate ratio, $\Delta e/\Delta r$, $\Delta\dot{e}/\Delta r$, $\Delta\ddot{e}/\Delta r$.

We can set an estimate of the time to stabilize the system. In Table II are given the times at which peak error occurred for a number of different transitions. Stabilization, in general, will have been accomplished prior to the time of peak error. In the experiments in which these data were obtained, four conditions were investigated for each change in $Y_c(s)$:

a. Alerted, certain (AC) in which the subjects had five sets of 15 or 16 pairs of transitions to and from the base condition of $Y_c(s)=8/s^2$. In each set all transitions were made to the same alternate $Y_c(s)$ so that the subject was certain about the nature of the transition. In addition, there was a 1000-cps audio alerting signal present while the alternate dynamics were in effect, and white noise in the base condition.

b. Not-alerted, certain (NC) in which the white noise was present all the time, but otherwise the sets of transitions were as in (1) above.

c. Alerted, uncertain (AU) in which the transitions in the run could be to any one of at least 12 different $Y_c(s)$, but the 1000-cycle tone was present to tell the subject that some transition had occurred.

d. Not-alerted, uncertain, (NU) where the transition was as in (c), but the white noise was present throughout, and the subject had no indication, other than through his tracking performance, that a transition had occurred.

We see in Table II that the average time of peak error varies between .7 and 1.0 second. If we subtract the detection times from the peak error times, we obtain an average interval between detection and stabilization (peak error) of about 0.25 second. Remembering that the observed detection time includes a period of about 0.5 second time devoted to identification, we find that stabilization occurs about 0.8 second after the error exceeds threshold. This is sufficient time for about three identifying movements to obtain the data for the three tests required to identify system characteristics.

Although the peak error times in Table II for the certain conditions are less than those for the uncertain conditions, the differences are not significant. For some of the transitions the peak error times for the alerted certain condition are significantly shorter than the non-alerted certain.

The very short peak error times in Table II imply that when the controller is well-trained at controlling all the dynamics with which he will be presented, he can make very rapid changes in his own characteristics to stabilize the system. It appears that once he has identified the system dynamics he can switch his mode of behavior suddenly from one form to another. At this stage of the adaptation process, he does not adjust his characteristics gradually. Gradual adjustment may take place when he is optimizing his characteristics.

4. Error Reduction Times. In Table III are the times to reduce the accumulated error to a criterion. The criterion was that the error had to reach less than 2σ of the fully adapted tracking error and remain there for at least one second. This criterion agreed in most cases with the subjective estimates of when the subject had adjusted to the new conditions and achieved good performance. The data in Table III are from the same experiment as those in Table II.

The error reduction times are between two and three seconds. The effects of alerting and certainty for reducing the error reduction times are evident in these results. The alerted certain times are significantly shorter than the non-alerted certain times. The alerted certain times are shorter than the alerted uncertain and the non-alerted uncertain times, but the differences are not significant. The sample size for the uncertain conditions was small (three samples/subject).

Conclusions

The models we suggest in this paper are tentative and still in the process of evaluation. They contain many simplifications and approximations and cannot be expected to represent human controller characteristics accurately in all situations. They do, however, provide a framework for experimentation by providing a means for predicting human controller response characteristics in specific testable situations. We are in the process of doing further tests of these models and expect that they will need considerable modification and elaboration in order to be consistent with the results obtained from these tests.

The model of Fig. 7 in its present form is easily simulated and with suitable approximation can be manipulated analytically. We do not expect that our present studies will lead to simpler models, because the human operator is not a simple mechanism. However, we do expect that the models that result will not be difficult to simulate. As such they should be useful as a means of understanding and predicting human controller behavior.

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Table I

Time to Detect Large Errors

Transition	Average Time Between Error > 3σ and Detection sec
$8/s^2 \rightarrow 16/s^2$	.5
$8/s^2 \rightarrow -16/s^2$	.4
$8/s^2 \rightarrow -8/s^2$	.5
$8/s^2 \rightarrow 4/s^2$	.5
$8/s^2 \rightarrow -4/s^2$	.5
$8/s^2 \rightarrow 2/s^2$	.6
$8/s^2 \rightarrow -2/s^2$	.5
$8/s^2 \rightarrow 16/s$	.6
$8/s^2 \rightarrow -16/s$	.4
$8/s^2 \rightarrow 8$	.6
$8/s^2 \rightarrow -8$	.8
$8/s^2 \rightarrow 4$	.4
Average	.5

*11. Systems," Quarterly Progress Report No. 64, Research Laboratory of Electronics, MIT, Cambridge, Mass. (July 1962)

Table II

Time of Peak Error (sec)

Transition	Condition AC*	NC*	AU**	NU**
$+8/s^2 \rightarrow -16/s^2$	1.12	1.40	2.32	1.55
$+8/s^2 \rightarrow +16/s^2$	1.08	1.34	1.53	1.53
$+8/s^2 \rightarrow -16/s$	0.59	0.73	0.92	0.95
$+8/s^2 \rightarrow +16/s$	0.53	0.59	0.55	0.93
$+8/s^2 \rightarrow +4$	0.19	0.30	0.25	0.26
Mean Peak Error Time	0.72	0.87	1.01	1.04
Mean Peak Error-Detection Time	0.17	0.10	0.33	0.41

* Average of 10 runs on each of two subjects

** Average of 3 runs on each of two subjects

Table III

Error Reduction Time (sec)

Transition	Condition AC*	NC*	AU	NU
$+8/s^2 \rightarrow -16/s^2$	3.35	4.15	4.75	6.1
$+8/s^2 \rightarrow +16/s^2$	2.35	3.94	4.5	3.1
$+8/s^2 \rightarrow -16/s$	1.79	2.82	2.9	2.8
$+8/s^2 \rightarrow +16/s$	1.77	1.83	1.8	2.4
$+8/s^2 \rightarrow +4$	1.04	0.99	1.3	0.85
Mean	2.06	2.75	3.04	3.06

* Average of 10 runs on each of two subjects

** Average of 3 runs on each of two subjects

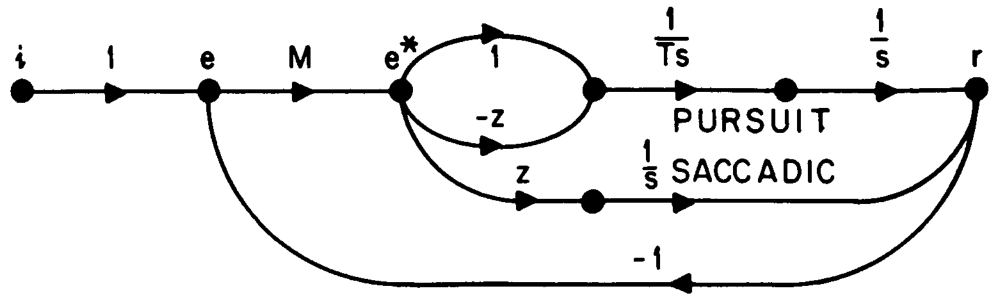


FIG. 1a

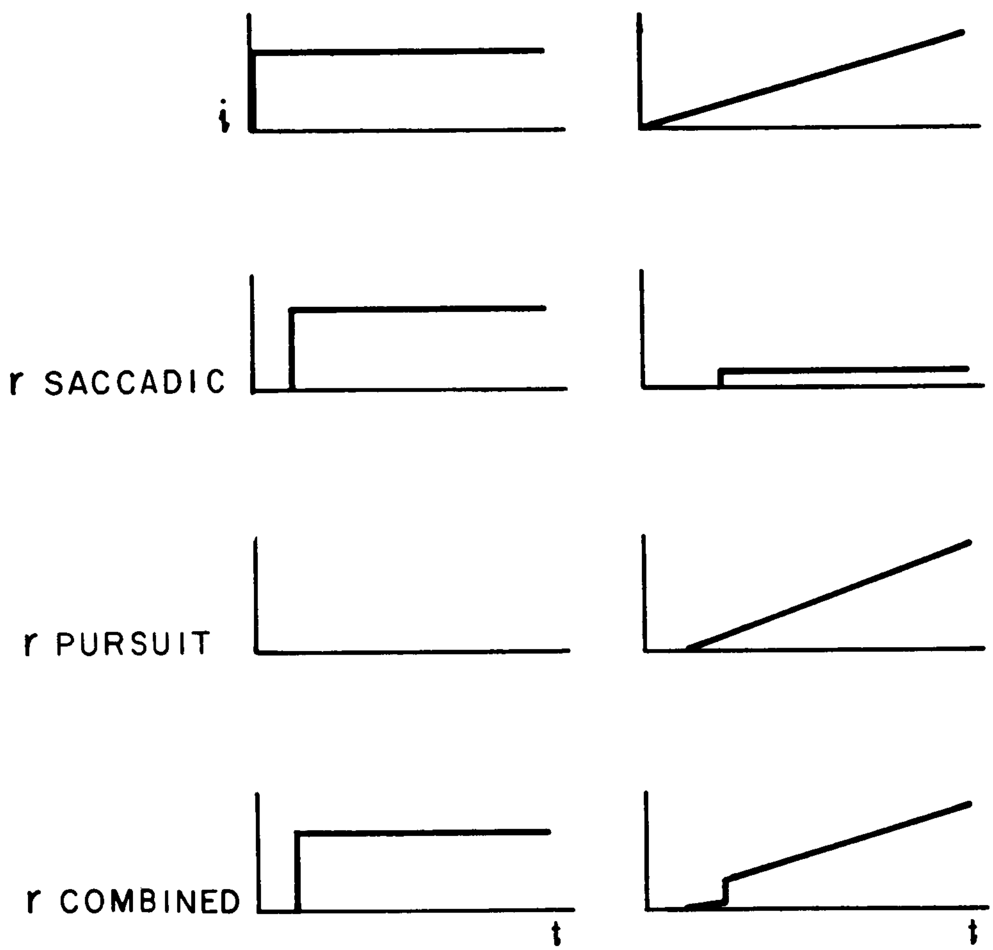


FIG. 1b

Figure 1 (a) Young eye movement model and
(b) its response to step and ramp

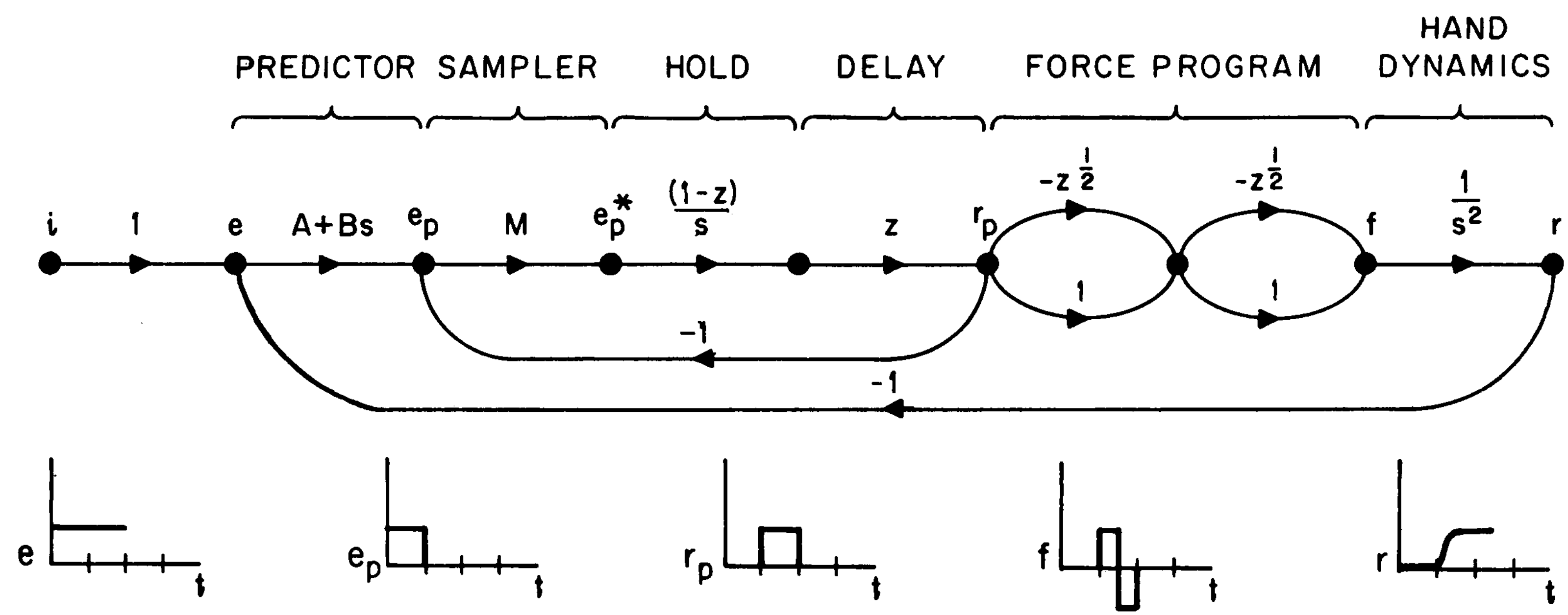


FIG. 2a

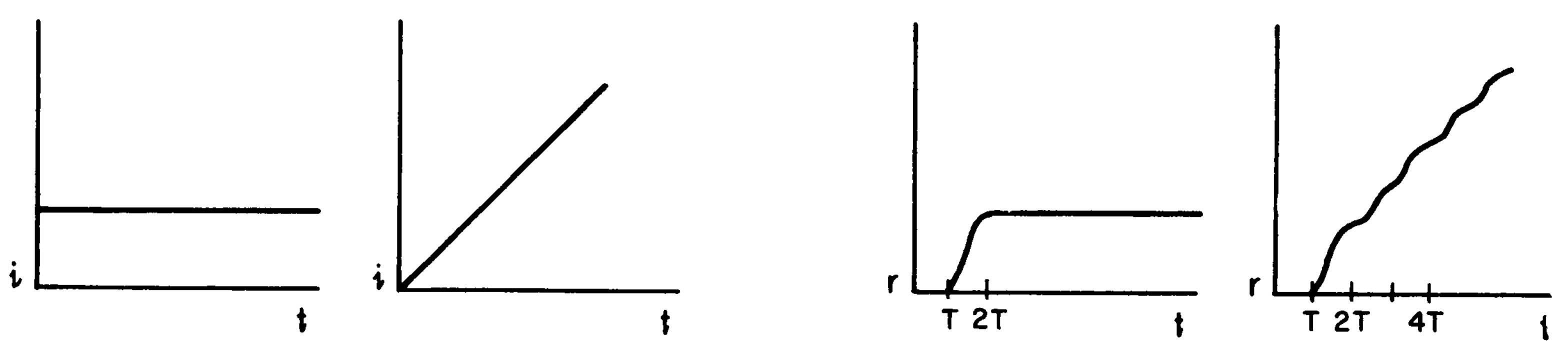
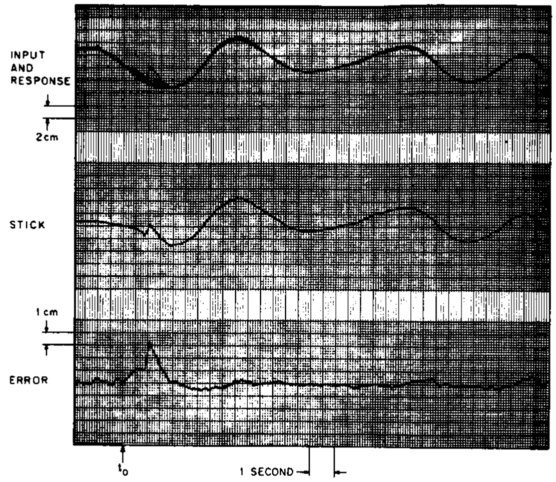
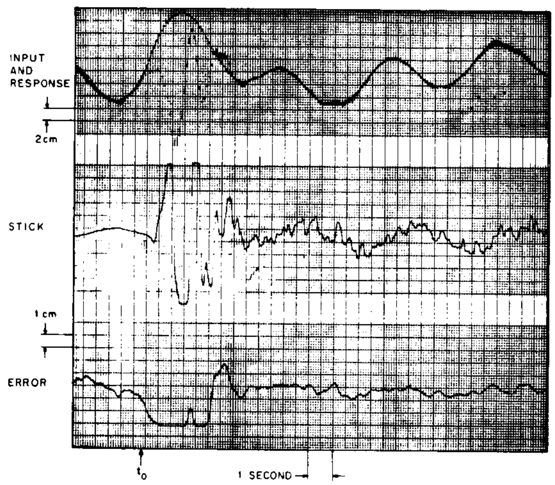


FIG. 2b

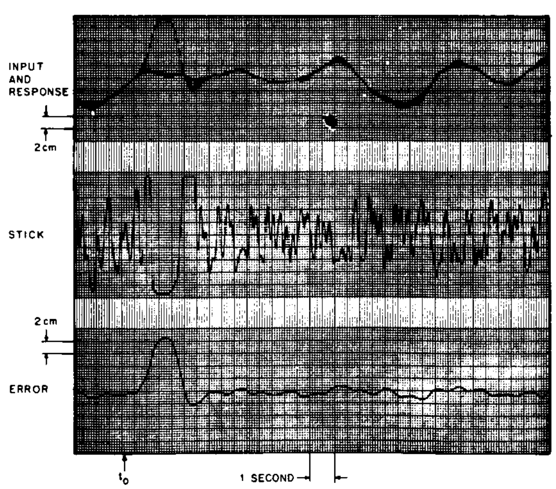
Figure 2 (a) Signal flow diagram of Lemay-Westcott hand tracking model, and (b) its response to step and ramp



(a) Controlled element $Y_c(s)=2$. At time t_o $Y_c(s)$ changed from +8 to +2.



(b) $Y_c(s)=4/s$. At t_o $Y_c(s)$ changed from +8 to $+4/s$.



(c) $Y_c(s)=8/s^2$. At t_o $Y_c(s)$ changed from $-4/s^2$ to $+8/s^2$.

Figure 3 Tracking records:

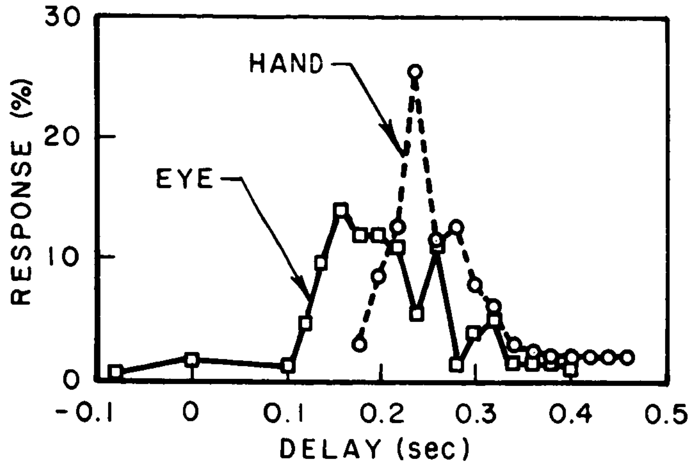


Figure 4 Eye and hand movement reaction times distributions to random step inputs (from Okabe, et al).[7]

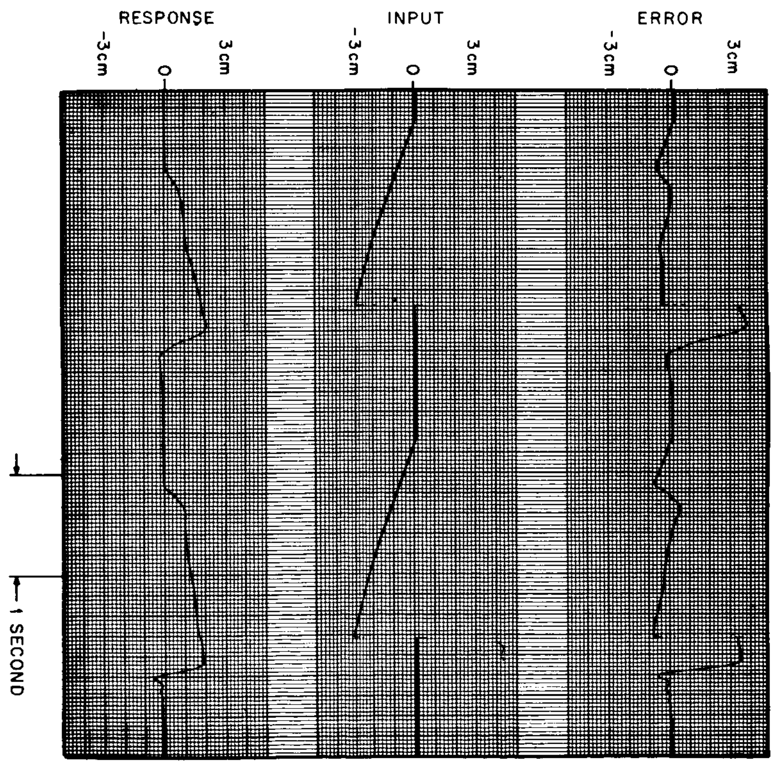


Figure 5 Records of hand tracking of ramps.

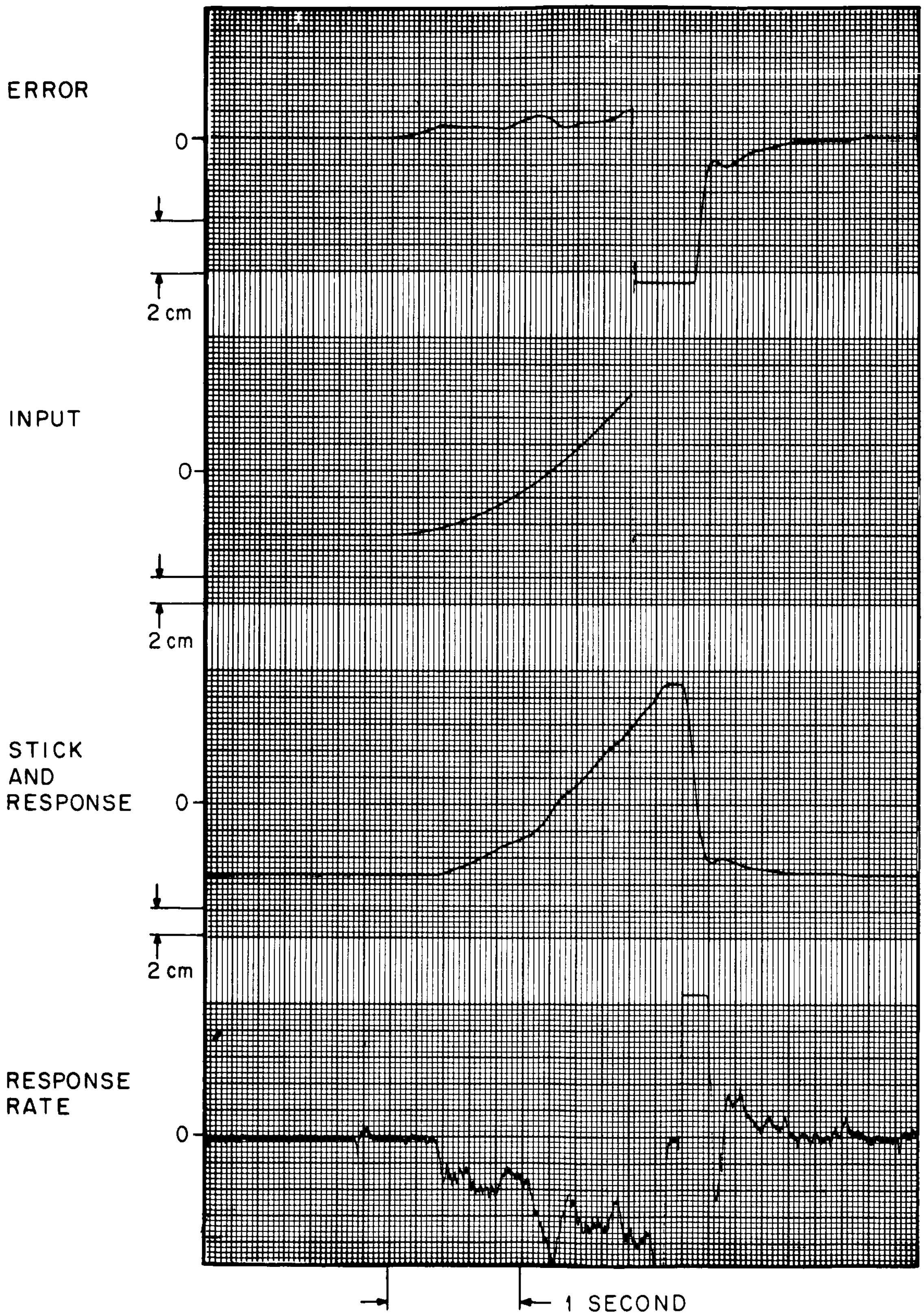


Figure 6 Records of hand tracking of a parabola.

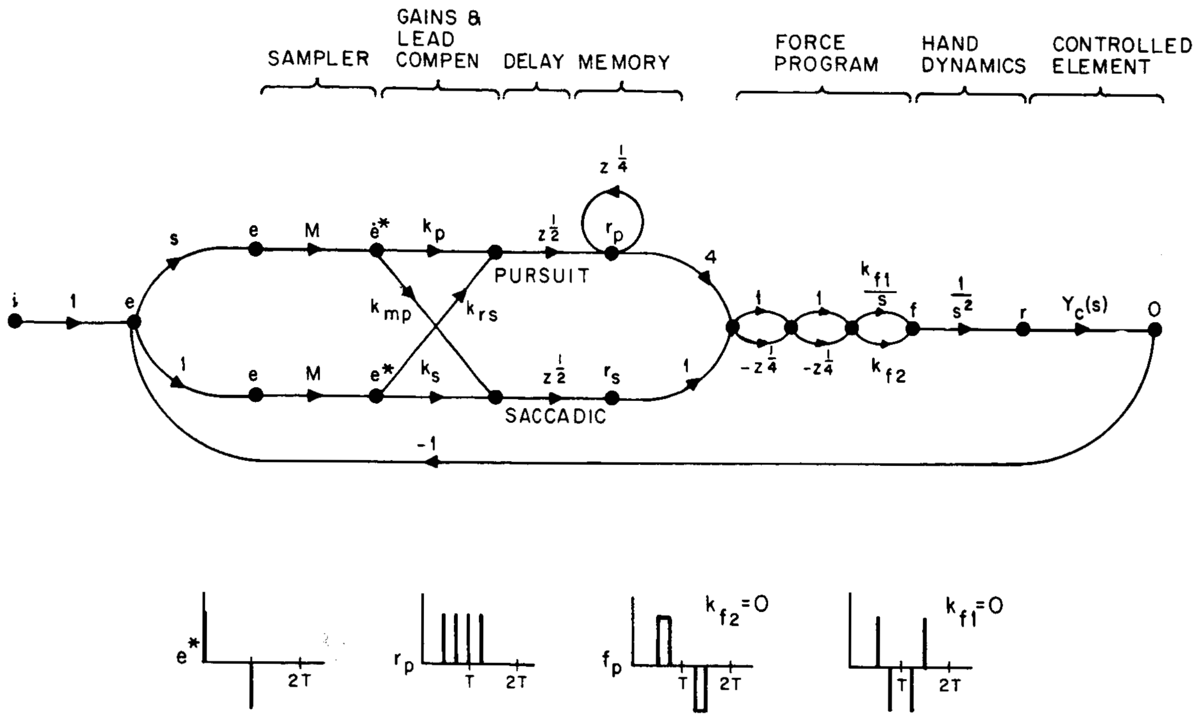


Figure 7 Proposed hand tracking model.

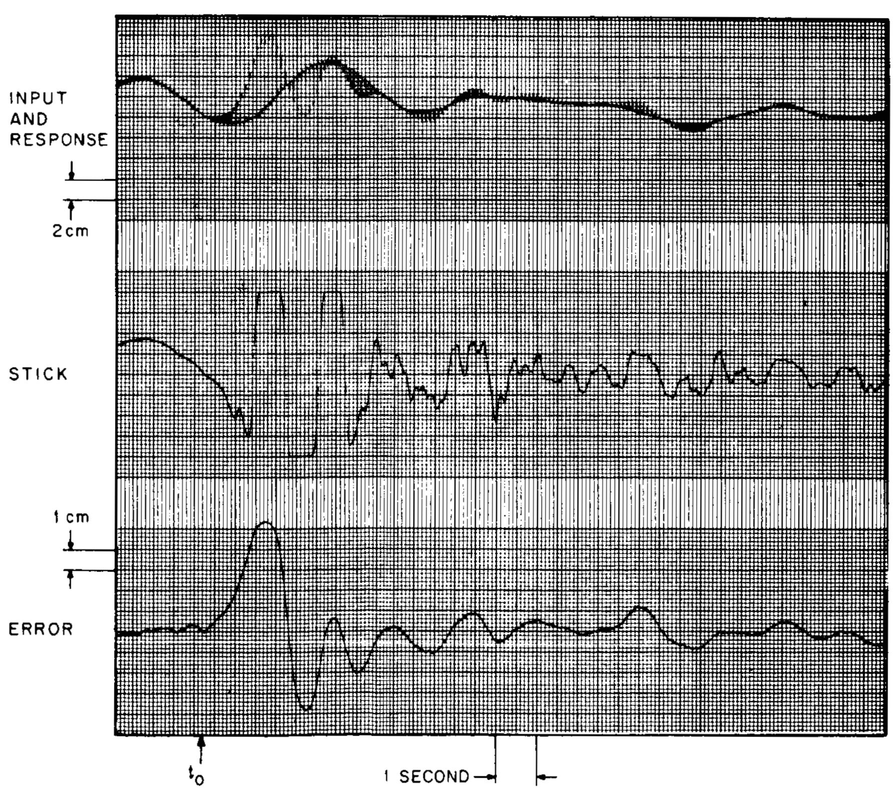


Figure 8 Tracking record for $Y_c(s)=K/s^2$ showing saccadic movements. At t_o $Y_c(s)$ changed from +2 to $-8/s^2$.

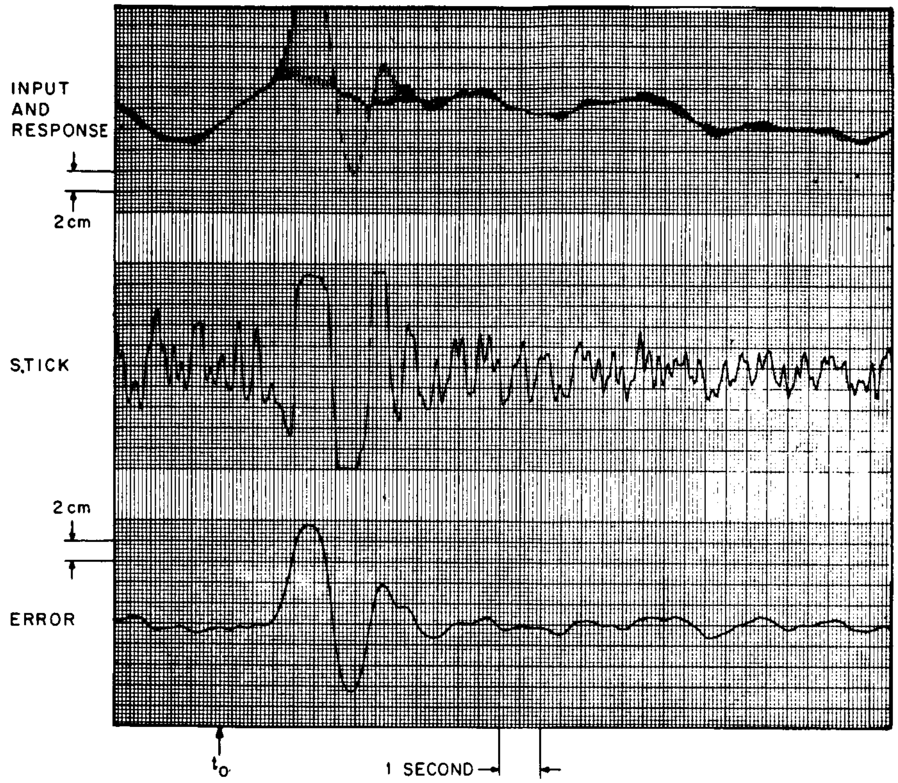


Figure 9 Tracking record for a change in $Y_c(s)$ from $+8/s^2$ to $-16/s^2$. The change occurs at t_o.

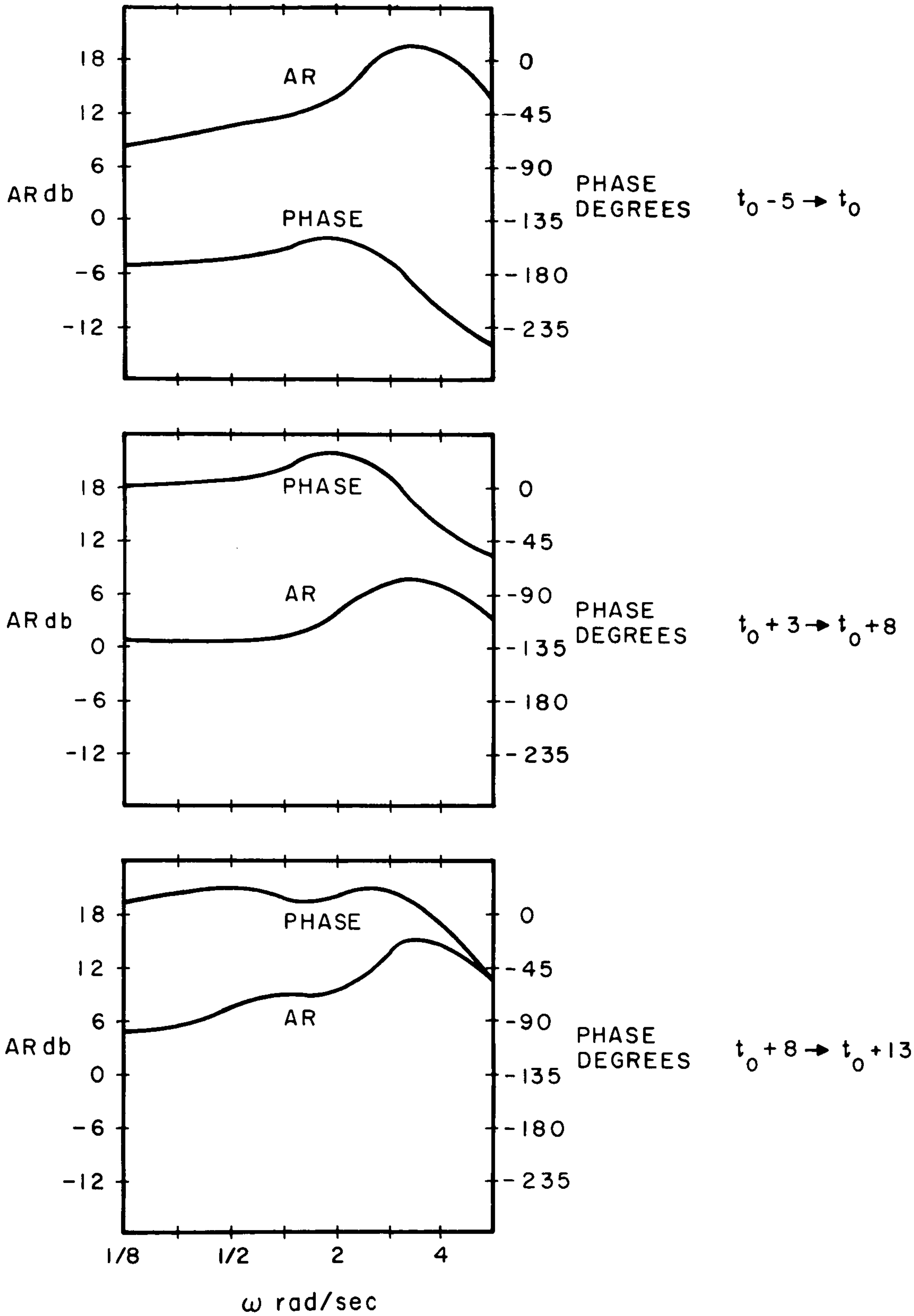


Figure 10 Bode plots of human controller describing functions obtained from successive five second samples of error and stick signals before and after a change in $Y_c(s)$ from $-4/s^2$ to $+8/s^2$.

III. STUDIES OF MULTI-AXIS CONTROL SYSTEMS

We have begun a series of experiments to determine how human operator control characteristics in multi-axis control systems differ from those in single-axis control systems, and to determine the extent to which the describing function models developed for single-axis control apply to the multi-axis situation. If we accept the model for the human controller proposed by Senders[1] in which the human behaves as a time-shared controller, then we would expect that the addition of a second axis to a single-axis control task would alter the human operator's characteristics in the first axis. This change in characteristics would result in an increase in tracking error and perhaps in a negative correlation of the error signals in the two channels. The correlation is due to the fact that when the controller is attending to one axis and reducing the error there, he is not likely to be attending to the other axis and the error in the unattended axis will increase. Of course, if the commutating rate is very high, the effects of the second axis will be small. If an increase in error and correlation between the signals in the two axes is observed the present single-axis models will have to be modified before they can be applied to the multi-axis situation.

[1] Senders, J. W., "The Human Operator as a Monitor and Controller of Multi-Degree-of-Freedom Systems," 4th National Symposium on Human Factors in Electronics, Washington, D. C., (May 1963).

The following is a brief description of the experiments we performed. The tracking situation was a conventional compensatory control situation with a scope display on which was presented an error dot and a circle. The scope was 12 cm in diameter. The target circle was .4 cm in diameter. The task was to keep the error dot as close to the center of the circle as possible. The system dynamics were pure inertia, $2/s^2$. The control was a two-axis spring-restrained joy stick which had a small inertia and small friction, and was spring restrained. The total excursion of the control stick was ±45 degrees in each axis. A flow diagram of the control system is shown in Fig. 1a.

Experiments were performed with no input forcing function in which the controller's task was merely to keep the system stabilized and to cancel out whatever noise was introduced by the analog computer and other apparatus. Experiments were also performed with an input forcing function that had a rectangular spectrum of bandwidth .08 cps, and RMS amplitude of approximately 2 cm.

Two subjects were used, both fairly experienced trackers. One of these subjects was a pilot who had considerable private flying experience. The subjects received only a small amount of training on each of the experimental conditions. The total training amounted to about two to three hours and was concentrated on those tasks which were most difficult. It is not likely that with this small amount of training the subjects had approached the limit of their performance. Rather, with considerably more training we expect that their performance would have improved.

The following were the experimental conditions that were investigated. With no input signal the subjects first tracked only in the X axis, with the error dot constrained so that it could move only in the horizontal X axis of the scope. Next the subjects tracked only in Y with the X axis of the scope deactivated. Then they tracked both in X and Y. Next various amounts of input coupling, as shown in Fig. 1b, were incorporated in the two-axis system. The input coupling corresponds to a rotation of the control with respect to the display. Rotations of 26 degrees, 45 degrees, and 90 degrees were used. Finally, two values of output coupling, as shown in Fig. 1c, were incorporated into the system. Coupling constants of .5 and 1 were used. After these experiments with no input were completed, the following experiments were performed with the input forcing function which had a rectangular spectrum of .08 cps bandwidth*: first X axis tracking only, then both X and Y axis tracking, then two-axis tracking with input coupling amounting to a 26 degree rotation, and finally two-axis tracking with output coupling of .5 were used. The average absolute error over successive one-minute periods of tracking were recorded for the X axis and the Y axis separately. Also, time-on-target scores were computed for successive one-minute periods. The output was considered on target if the error was within the 0.4 cm target circle. Time-on-target scores for the X axis and the Y axis and both X and Y axes were obtained.

The results of the experiments for the two subjects are shown in Table 1. We see that with no input signal both

*The RMS amplitude of the input was about 2 cm.

subjects could maintain the error dot within the target circle almost all of the time and had a time-on-target score of about 100 per cent and error scores that were very small. For both subjects there were small differences between X tracking and Y tracking. These differences are probably the result of the fact that the subjects were more experienced in controlling in X than in Y and that the control was somewhat better human engineered for X axis movements (left-right movements) than for Y axis movements (forward-backward movements). The addition of the second axis to the single-axis test produced an increase in errors and a decrease in time-on-target scores. Similarly, the incorporation of input coupling increased the errors and decreased the time-on-target scores relative to the two-axis tracking without coupling. The changes are relatively small for couplings of 45 degrees or less, but are very large for an input coupling of 90 degrees. In Fig. 2 is a plot of the error and time-on-target scores as a function of input coupling. Output coupling leads to no marked increase in error beyond that observed in the two-axis uncoupled situation. The reason is that with no input forcing function the system output remains very close to zero and the effects of output coupling are very small. Similar results were observed with the input forcing function. The addition of the second axis degrades performance, the addition of a moderate amount of input coupling degrades performance slightly. But with an input signal, the addition of output coupling produces a considerable degradation in performance, a result that was not observed without the input forcing function. With the input signal present, the output does deviate from zero and the output coupling terms are important. We note that in almost all cases scores of time-on-target in both X and Y simultaneously are very nearly equal to the product of TOT_X and TOT_Y, thus indicating that the probability that responses will be on target in X is independent of the probability that it will be on target in Y. This result is a small indication that responses in the two axes are performed independently and time-sharing, if it exists, does not affect the error signal.

We might interpret the fact that performance worsened in X axis when the Y axis was added as an indication that the single-axis models must be modified for multi-axis control situations, and the fact that performance was degraded when input coupling was added as an indication that the subjects did not decouple this system completely, or that the necessity to decouple led to degradation of tracking.

On the other hand, the changes in performance may be due simply to lack of training with the two-axis and coupled tasks. There are two indications that the effects of lack of training may be important. First, even for small amounts of input coupling (26 degrees) the error increased. Input coupling is equivalent to a rotation of the control with respent to the display. We would expect that with training subjects would learn to make movements in the correct direction and compensate for the rotation. This they apparently did not do. Second, the information transmission rates in this task were very low. In single-axis continuous tracking information, transmission rates as high as 8 bits/sec have been reported. Information rates as high as 17 bits/sec have been observed in disontinuous or pointing tasks.[2] The highest single-axis information rates observed in this experiment are less than 1 bit/sec. Thus, it does not appear that the subjects are being loaded to the limit of their information transmission capacity, and we might expect that with further training they could control each of two axes as well as a single-axis. We plan to repeat this experiment with more highly-trained controllers to see if this result is obtained.

[2] Elkind, J. I. and L. T. Sprague, "Transmission of Information in Simple Manual Control Systems," IRE Transactions on Human Factors in Electronics, Vol. HFE-2, No. 1, March 1961.

TABLE I

AVERAGE ABSOLUTE ERROR AND FRACTION TIME-ON-TARGET SCORES* FOR TWO SUBJECTS

CONDITION	$\overline{\lvert error_Y \rvert}$ cm	$\overline{\lvert error_X \rvert}$ cm	TOT_Y	TOT_X	TOT_{XandY}	$(TOT_X)x(TOT_Y)$
		NO INPUT				
X Only		.023 .062		1.00 1.00		
Y Only	.055 .095		1.00 .91			
X and Y	.081 .127	.097 .085	.98 .77	.95 .89	.93 .71	.93 .69
X and Y 26° Input Coupling	.135 .160	.129 .099	.92 .73	.80 .91	.76 .69	.74 .66
X and Y 45° Input Coupling	.226 .275	.176 .175	.77 .47	.78 .85	.64 .41	.60 .40
X and Y 90° Input Coupling	1.05 .94	.92 1.01	.21 .27	.29 .20	.10 .07	.06 .05
Y and Y 0.5 Output Coupling	.174 .174	.170 .101	.88 .82	.85 .97	.72 .80	.75 .80
X and Y 1.0 Output Coupling	.111 .173	.130 .098	.94 .85	.92 .96	.86 .83	.87 .82
		R.08 INPUT				
X Only		.061 .172		1.00 .50		
X and Y	.243 .254	.182 .283	.75 .37	.74 .37	.58 .15	.55 .14
X and Y 26° Input Coupling	.393 .353	.241 .271	.56 .30	.63 .49	.30 .15	.35 .15
X and Y 0.5 Output Coupling	.535 .545	.374 .419	.49 .21	.47 .28	.26 .05	.23 .06

*Each entry is the average of three measurements on a single subject. In every case the upper entry is for Subject 1 and the lower entry is for Subject 2.

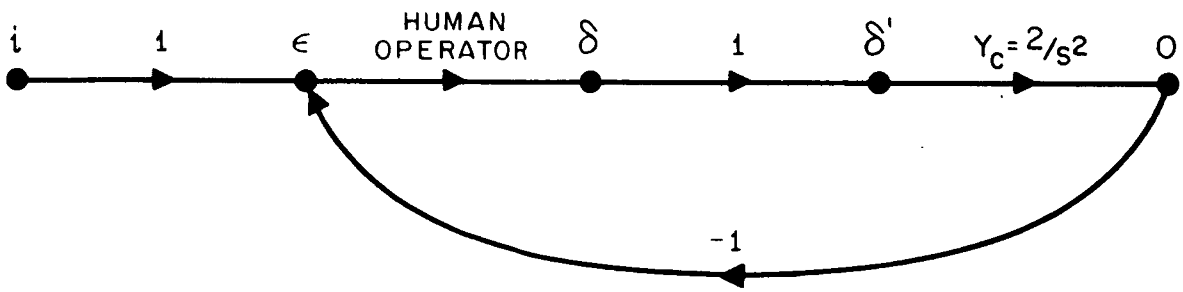


FIG. 1a FLOW DIAGRAM OF ONE AXIS OF CONTROL SYSTEM

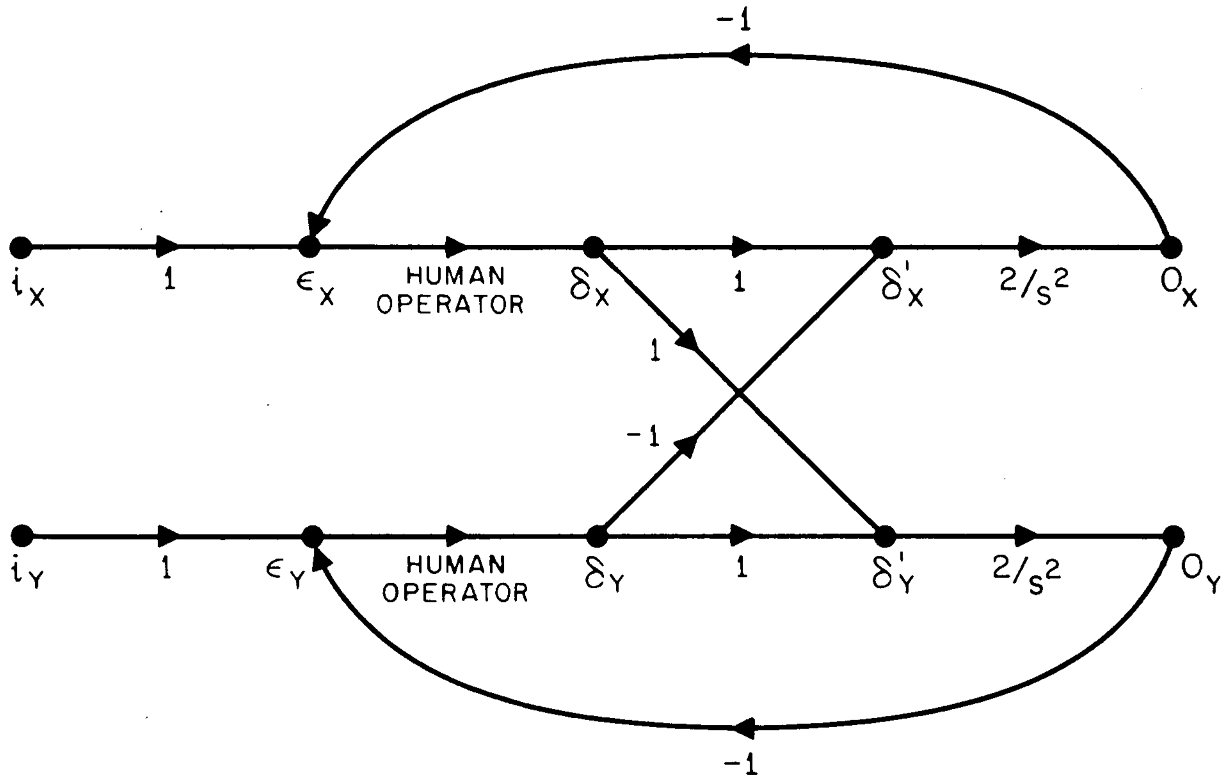


FIG. 1b TWO AXIS SYSTEM WITH 45° INPUT COUPLING

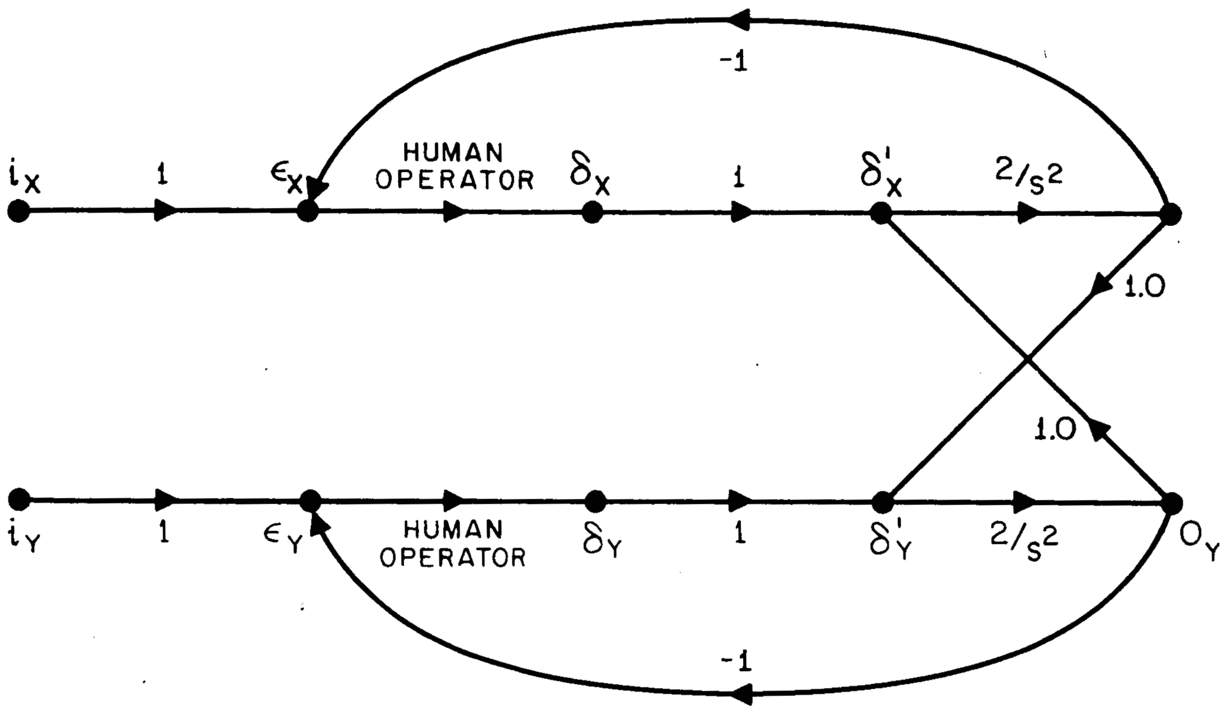


FIG. 1c TWO AXIS SYSTEM WITH OUTPUT COUPLING OF 1.0

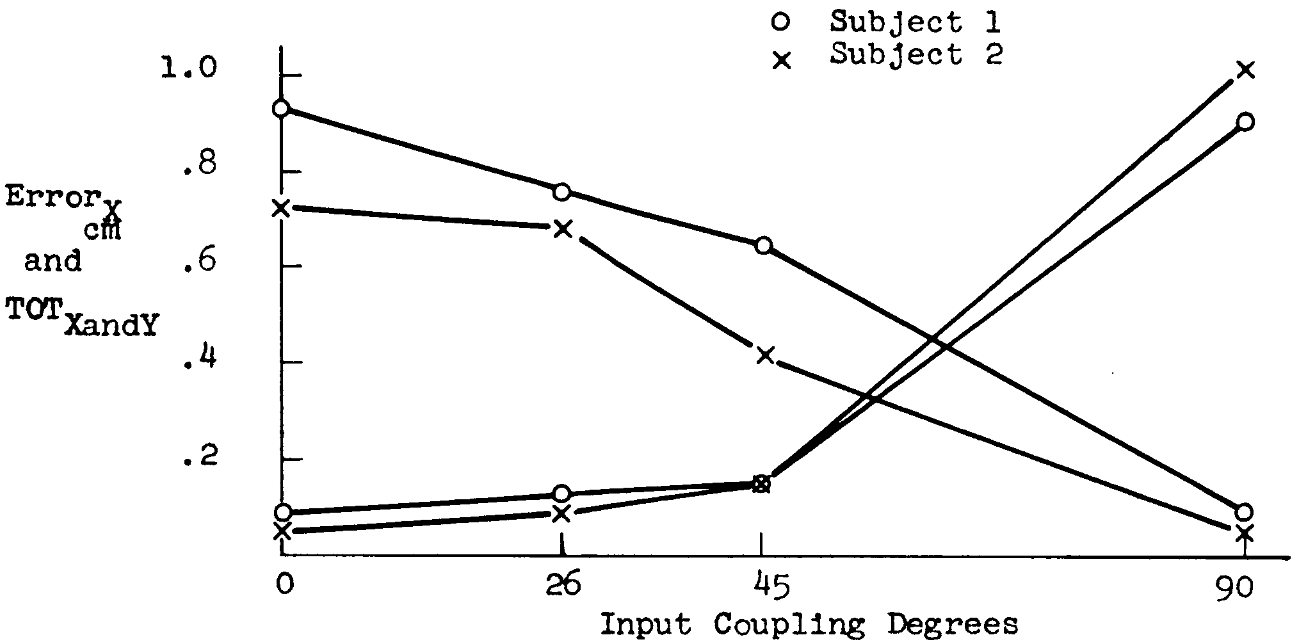


FIG. 2 ERROR AND FRACTION $\mathrm{TOT}_{X\ and\ Y}$ VS. INPUT COUPLING WITH NO FORCING FUNCTION